Meta-Optimization for Optimal Power Flow

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- Planning and operations for electricity grids are carried out by solving various non-convex constrained optimization problems
- Computational complexity can impede tractable real-time scheduling, integrating volatile renewables and mitigating emissions
- We propose a form of *meta-optimization* to predict a good initialization for rapid adaptation to new system conditions

1) Motivation

- Operating electricity grids requires dispatching generation to meet load at minimum cost, respecting reliability/security constraints. This involves solving a non-convex and non-linear constrained optimization problem, **Optimal Power Flow** (OPF) model.
- Under increasing variability of system conditions due to renewable integration and distributed energy resources, such optimization problems are increasingly complex[1] with limited solve-time.
- Typically, OPF is approximated by a convex form, ignoring certain constraints. This can however lead to various issues and inefficiencies.
- Our aim is to find a model for *fast convergence* of OPF.

3) Proposed Methodology

- **Scenario generation**: Use pglib[3] grid cases and create $L_{\text{train}}+L_{\text{test}}$ new scenarios by mutating grid parameters.
- **OPF Solver[5]:** Take a formulation x along with the initial solution guess y_0, and solve for y^*.
- **Model:** NN trained to output solution initialization (y_0^{red}) for OPF, given formulation (x^{red}).
- **Conventional Loss:** Quality metric on initialization (e.g. MSE to final solution in convex case).
- **Meta-Loss:** Sum over all scenarios j of the number of IP steps, (N_{IP}^j). Each scenario j uses initialization $y_0^j = \mathrm{NN}(x; w)$
- **Meta-Optimization:** Given the non-differentiable loss-function, we use gradient-free optimization (GFO) with I iterations. Here, we use the Particle Swarm Optimization method.
- **Compression/Decompression** Reduce/expand the grid formulation, preserving key electrical properties[4], to/from a size that the meta-optimizer has been trained for.

$w \leftarrow \mathit{initialize!}$
for $i \leftarrow 1, I$ **do**
  $\mathit{metaloss} \leftarrow 0$
  for $j \leftarrow 1, L_{\text{train}}$ **do**
    $x^j \leftarrow \mathit{scenario}[j]$
    $y_0^j \leftarrow \mathrm{NN}(x^j; w)$
    $y^*, N_{\text{IP}} \leftarrow \mathsf{OPFSolver}(x^j; y_0^j)$
    $\mathit{metaloss} \mathrel{+}= N_{\text{IP}}$
  end for
  $w \leftarrow \mathsf{GFO}(w, \mathit{metaloss})$
end for

Algorithm 1: Meta-optimization of OPF

2) Optimal Power Flow

- Given an **input parameter vector** x (specifying grid properties) the objective of OPF is to minimize the total generation cost:

$$\min_y \sum_{g \in G} C_g(x, y), \tag{1}$$

- This is subject to various constraints representing power balance, current flows, and generation capacities.
- The **solution** y^* of the OPF includes the power output of each generator and the (complex) voltages at each bus.
- Typically, **interior-point** (IP) methods are used (e.g. Ipopt).

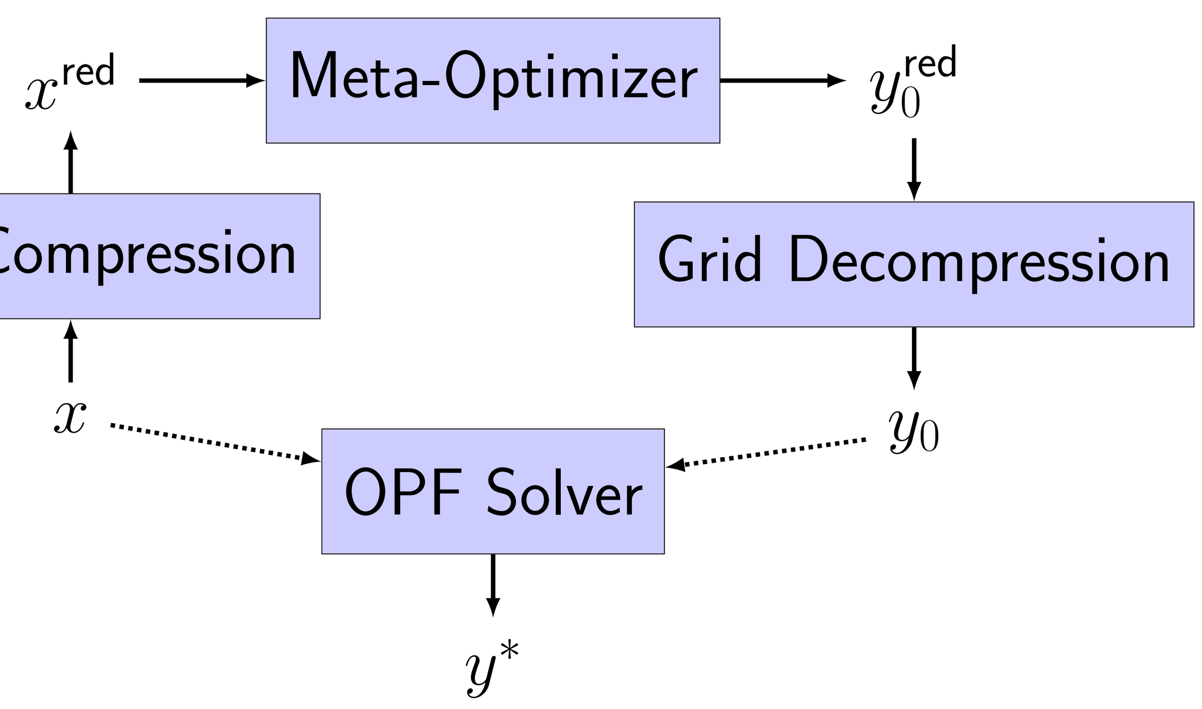

Figure 1: Proposed workflow of meta-optimized OPF

4) Provisional Results

- We examine partial warm-starts through primal variable initialization. Expressing full (100%), partial (primal) and heuristic initialization (0% baseline), Efficiency(%) $= 100\frac{N_{\text{heur}}-N_{\text{primal}}}{N_{\text{heur}}}$.
- Comparison of a conventional NN supervised learning using a MSE(y_0^{NN}, y^*) objective on the metaloss, followed by the meta-training.

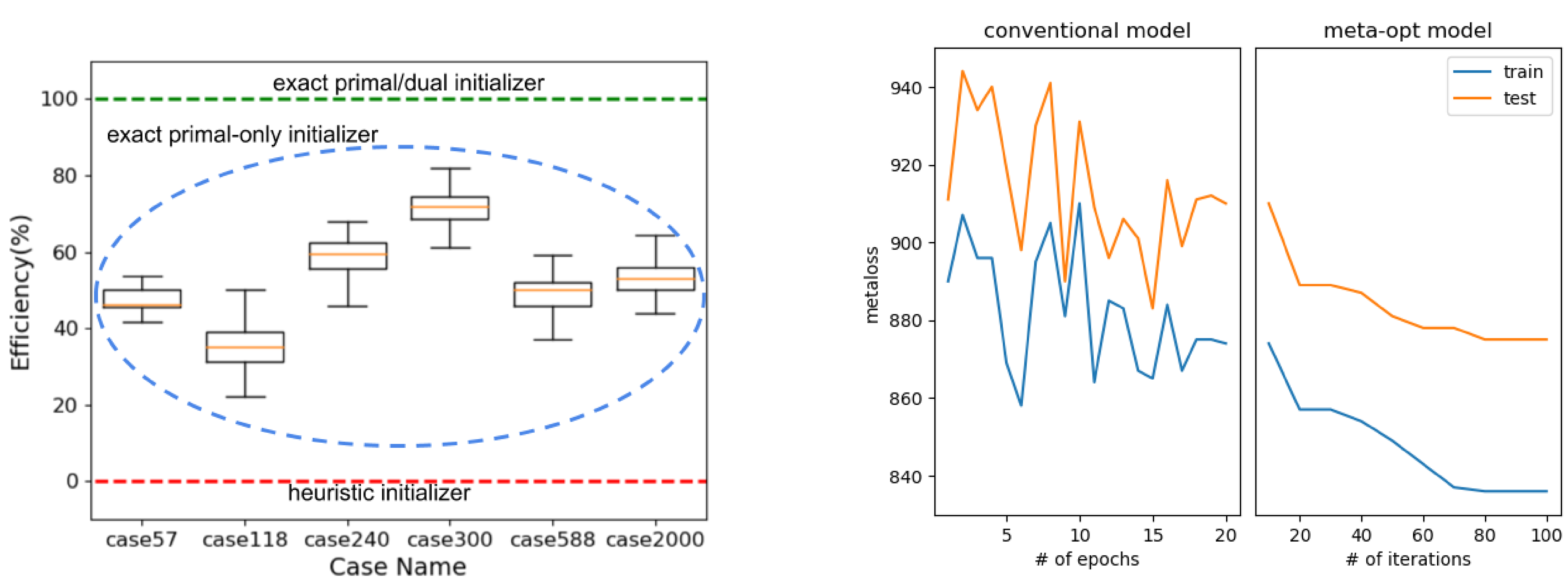

Figure 2: Left: Efficiency of primal initialization. Right: Effect on meta-loss using a supervised learning approach

5) Challenges and Future Directions

- **Meta-Optimizer Training:** In a typical meta-optimization settings, gradient-based updates are used. However, typical IP methods are second order so it is non-trivial to back-propagate through the solver[2].
- **Compression:** Designing a suitable compression algorithm that works over many types of grids of different sizes is an important step.

1. Gholami, A., Ansari, J., Jamei, M., and Kazemi, A. Environmental/economic dispatch incorporating renewable energy sources and plug-in vehicles. IET Generation, Transmission & Distribution, 8(12):21832198, 2014
2. Amos, B. and Kolter, J. Z. Optnet: Differentiable optimization as a layer in neural networks. CoRR. URL arxiv.org/abs/1703.00443
3. https://github.com/power-grid-lib/pglib-opf
4. Zhifang Wang, Anna Scaglione, Robert J. Thomas, Compressing Electrical Power Grids, IEEE International Conference on Smart Grid Communications, 2010
5. Carelton Coffrin, Russel Bent, Kaarthik Sundar, PowerModels.jl: An Open-Source Framework for Exploring Power Flow Formulations, URL arXiv:1711.01728v3